A Fully Automatic Novel Method to Determine QT Interval Based on Continuous Wavelet Transform

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Abstract: *Nowadays, automatic recognition algorithm is being frequently utilized to extract the information concerning cardiac abnormalities. In this study, a fully automatic novel method based on the continuous wavelet transform (CWT) was developed for QT intervals in various ECG signals. Especially, the determination of T-wave end is the paramount problem to be solved.The developed method was performed to find the beginning of QRS complexes and the end of T-wave. The proposed algorithm was tested on MIT-BIH-NSR database given by QT database, then, it yielded the scores 15.17 milliseconds and root-mean-square error of 17.19 milliseconds at silver standard, 19.22 milliseconds and 20.22 milliseconds at gold standard, respectively. In conclusion, the proposed algorithm is a fully automatic method to attain a high performance in the calculation of QT intervals at various ECG signals.*
Keywords: *ECG Signal, QT interval, ECG signal classification, Pan-Tompkins Algorithm, Continuous Wavelet Transform*

1. Introduction

Electrocardiography(ECG) is represented as the cardiac activity reflecting its electrical activity in heart muscles. Since the invention of the Einthoven rules, it has been used as a diagnostic feature to identify electrical propagation of cardiac muscles, which means that it has valuable information regarding cardiac situation of a patient. Generally, the cardiac activity is separated into two parts, depolarization and repolarization indicating contraction and relaxation of heart muscle. Therefore, some sort of abnormal electrical propagation are reflected in ECG, then, one can extract vital features in cardiac level of patients.

Namely, ECG consists of two waves (P and T) and one complex (QRS) which are illustrated in Fig.1.
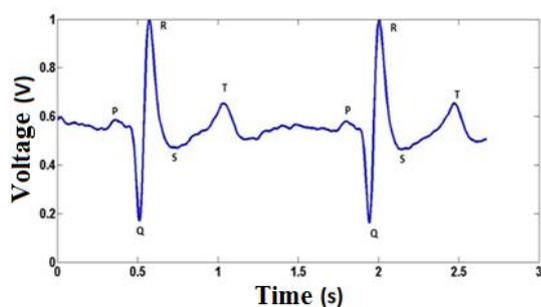
Fig. 1. ECG Signal

P wave denotes the contraction of atrial muscle pumping the blood into the ventricles. QRS complex represents the stimulation of right and left ventricles. Right and left ventricles perform to pumps venous blood into the pulmonary and fresh blood through the artery. All of the works to be done are automatically achieved which means that the heart is an autonomous system. Synchronization is provided by the electrical stimulation within specific intevals(QT inteval, PR segment). As a results, any irregularities including mechanical and electrical abnormalities in heart synchronization causes to fail the heart muscle leading to sudden death [1].

QT interval, one of the most important duration, is defined as the time lapse between the beginning of the depolarization and the end of the repolarization in heart ventricles. There is a strong relationship between QT intervals and several heart diseases, in which it is utilized to diagnose some of the abnormalities [2].

Before the advancement of computer programming paving a way for easily solving difficult problems, Experts and Cardiologists decided that electrical activities of heart had whether abnormalities or not , by examining the ECG signals in terms of duration and amplitude features, which were literally manually measured.

However, the performance of the manual QT measurement was reduced because of long records, fatigue in reading, individual evaluation and ECG device feature [2]. In addition, only 25% of cardiologists who had no experience in electrophysiology could assign correct marks of QT interval locations[3]. In long records, manual measurements had a problem with selecting representative beats indicating instantaneous cardiac situations due to the non-stationary feature of ECG [4].

For these reasons, automatic algorithms have been developed to determine the beginning of the QRS complex and the end of the T-wave.

Numerical methods based on the derivative feature were performed to measure QT intervals [2,6]. In despite of reduction in the calculation of the cost, the performance of QT measurement was affected by T wave amplitude, isoelectric baseline changes, and false detections. Also, the T-wave slope and the isoelectric level are required to be applied these algorithms. In addition, intra-beat variations have a negative effect on detecting boundary points in the ECG pattern.

Some of the methods related to formulation of ECG patterns were established to analyze the start and end points of ECG waves [7,8]. Although, these algorithms can be effectively applied to classify basic waves such as QRS and T, they had a poor score for the determination of boundary points due to the vexing problem which was defined as trying to use a deterministic method applying a non-deterministic problems [9].

In order to process non-deterministic ECG signals, neural network applications were developed [10-12]. Neural networks can be efficiently achieved to measure QT intervals regardless of frequency characteristics of ECG, after training them. However, this process requires too long training data, and is not an automated method.

There are some methods which are independent of ECG level and implemented in the frequency domain [13]. It is noteworthy that the measurement performance decreases with significantly removing waveforms,even the algorithms are fully-automated. On the other hand, these algorithms cannot be achieved to apply on the signals obtained from different channels of ECG because T wave and QRS complexes orientations change.

Due to all reasons explained above, in this study, a novel full-automatic algorithm based on continuous wavelet transform (CWT) was proposed to recognize the beginning of depolarization and the end of repolarization in heart ventricles. In the presented algorithm, the ECG signals were preprocessed by filtering and flattening. Then, the ECG boundaries are marked by using CWT. The algorithm performance was evaluated in terms of gold and silver standards which are the comparisons with manual annotations and comparison of standard automatic algorithms, respectively.

2. Method

QT intervals in ECG records were computed in this study and the evaluation was performed by comparing achieved and expected results (annotations) . QT interval detection and evaluation steps of the algorithm will be investigated in the subsections.

2.1. QT Interval Detection
2.1.1. Preprocessing

An ECG record is a quite rough signal due to ambient and measurement noises, undesirable effects on the physical conditions such as patient's breathing, the activities of other organs. To eliminate such conditions, the ECG records were filtered by a band pass FIR (Finite Impulse Response) filter with 0.5 Hz and 40 Hz cut-off frequencies since the electrical signals produced by the human heart during the pulse were in this frequency band [6]. The mathematical description of the filter is

$$y(n) = \sum_{k=0}^{N} c_k \cdot x(n-k) \qquad (2.1)$$

where c_k is a constant scaling parameter, x is to be filtered the ECG record, y is the filter output, n is the current time step and $N = 330$, the filter order. The filter order is selected such a large value which is an appropriate number containing one electrical cycle of the heart in order to take the desired frequency window of the records exactly. On the other hand, the computational time for filtering is increased, which means that such a selection was not suitable for real time applications.

Coiflet-1 type continuous wavelet transform was applied to the filtered ECG record. Type 1 represents that the used wavelets are orthogonal wavelets. Scaling function level of the wavelet is selected as 9 with respect to the frequency band of T wave end pattern [14]. The resulting signal was used for QT interval detection analysis as explained in the following sections..

2.1.2 QRS Complex Starting Point Determination

Firstly, *QT Pattern* signal which will be used for determination of QRS complex starting and T wave end points was defined as

$$QT\ Pattern = (CWT\ Output)^2 \qquad (2.2)$$

where *CWT Output* is the signal obtained after CWT analysis. This mathematical trick was used to make higher and lower amplitude parts of the signal more apparent. The amplitude of the *QT Pattern* is high in the vicinity of the R peaks, therefore to be analyzed signal for QRS complex starting point *QRS Pattern* is defined with a piecewise function as

$$QRS\ Pattern(i) = \begin{cases} 0 & ,\ QT\ Pattern(i) < A \\ QT\ Pattern(i), & otherwise \end{cases} \qquad (2.3)$$

where A is equal to three times mean values of *QT Pattern*, i is an integer number from 1 to ECG record length. This comparison level to produce *QRS Pattern* was found with a heuristic approach.

In *QRS Pattern*, all the peaks are possible R peaks of the evaluated ECG record, and the highest amplitude peaks in the defined scan range are R peaks of the ECG record. R

peak scan range was selected as ±160 milliseconds because of the largest healthy QRS duration[15].

By using R peak locations information, the QRS complex starting points can be determined. However, the directions of the R peaks in the ECG record should be considered. The R peak directions may be positive or negative based on its record lead. Therefore, the piecewise function (2.4) considering R peak directions was used to mark QRS complex starting point as

$$QRS_{Start}(i) = \begin{cases} Q_{Min}(i) - 8\,ms, & R_{Peak}(i) \text{ is positive} \\ Q_{Max}(i) - 8\,ms, & R_{Peak}(i) \text{ is negative} \end{cases} \quad (2.4)$$

where QRS_{Start} is QRS complex starting points, i is an integer number from 1 to ECG record length, Q_{Min} and Q_{Max} are minimum and maximum points around left side of R peaks respectively and R_{Peak} is investigated R peak of the ECG record. It is obvious that minimum or maximum levels were not directly marked as QRS complex starting points. Eight millisecond subtraction was used to catch points at isoelectric level. The first phase of the QT interval determination was finalized by labeling the starting points of QRS complexes.

2.1.3 T Wave End Point Determination

In the previous section, it has been declared that direction of R peaks could be positive or negative. The same situation is also valid for T-wave of the ECG records. For correctly positioning the T-wave end on the ECG, the directions of the T-waves should be identified as positive or negative. For this purpose, the method shown in Fig.2 was used. Firstly, RR interval for each beat shown in Fig.1 was calculated by the times between consecutive R peaks. Secondly, the highest and lowest amplitude points were marked as possible T-wave peaks of the ECG record by scanning the next half of the RR interval from the corresponding R peak. Finally, the direction of T-wave peaks whether positive or negative was determined by comparing the area under the ECG curve and the shaded area as shown in Fig.1. As a result of this decision mechanism, the highest or lowest possible T-wave peak points previously marked were assigned as T-wave peaks.

The amplitude of the signal achieved after CWT analysis is relatively low around T-waves while these parts of the signal were critical for the determination of T-wave end points. To focus the desired signal windows, piecewise function expressed in (2.5) was used.

$$T\,Pattern(i) = \begin{cases} 0 & , QT\,Pattern(i) > 0.05 \\ QT\,Pattern(i), & otherwise \end{cases} \quad (2.5)$$

where $T\,Pattern$ represents the signal to be used for detection of T-wave ends and i represents an integer from 1 to ECG record length. The threshold value, 0.05, was selected to remove the all frequency peaks produced by continuous wavelet transform at T wave except the end of the repolarization, in ventricles, T wave end. Normally, T wave frequency peaks generated by the continuous wavelet transform establish several critical points indicating the turning place on the ECG signal. One of them, the T wave end possesses the three crosspoints which are descending, ascending and steady line, respectively. The threshold values clarify these lines which can be detectable. Achieved *T Pattern* signal was normalized before using it, because it contains signal parts with only weak amplitudes. Even if the high-amplitude parts are cleaned, the *T Pattern* may still contain sections related to the T-wave ends and that may cause faulty evaluation. The Clear Area Region (CAR) shown in Fig.3 is a window starting from 20% of RR interval in the rear of R peaks up to the previously determined T-wave peaks. The CAR of each beat was suppressed in *T Pattern* to eliminate the parts irrelevant to the end of the T-waves. The rest of the signal was used to detection of T-wave end positions.
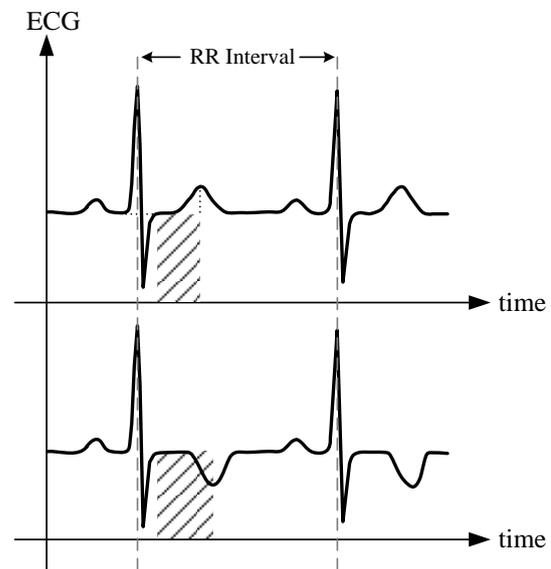
Figure 2: Positive or Negative T-wave Peak Determination

In the last step of QT interval determination, the algorithm focused the right hand sides of the previously determined T-wave peaks. Therefore, the peaks following the T-wave peaks of the cleared signal were utilized. The decision mechanism shown in Fig.4 was executed to mark T-wave ends of each beat in ECG record. For previously found each T-wave peak in ECG record, the peaks of the cleared were scanned in T-wave scan range. When both the 2nd and 3rd peaks are available in the cleared , the T-wave end position of the beat was assigned as the average position of the 2nd and 3rd peaks. On the other hand, the T-wave end position of the beat was assigned as the position of 2nd peak if it is available, but the 3rd one is not. Otherwise, it was assumed that the T-wave end of the beat is not detected.

QT intervals of the beats in ECG record was calculated by using the following function

$$QT\,Interval(i) = T\text{-wave end}(i) - QRS\,start(i) \quad (2.6)$$

where $QT\ Interval(i)$, T-*wave end*(i) and $QRS\ start(i)$ are

QT interval value, T-wave end position and QRS complex start position of the ith beat, respectively.
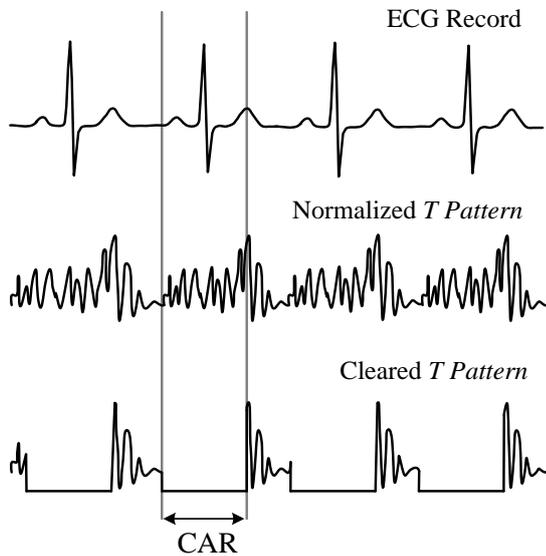
Figure 3: Acquiring the signal to be used for calculation of the T-wave end points
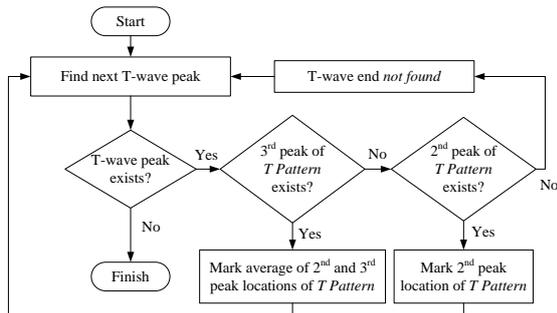
Figure 4: T-wave end position determination flowchart

2.2 Evaluation Procedure

QT interval values determined by the proposed algorithm in this study and received from the annotations were compared in terms of mean error and standard deviation error. After that the score of the algorithm for evaluated ECG record database was calculated as mean squared error (MSE) of the previously found QT interval mean errors for each evaluated ECG record.

3. Experiment

The experiment was performed by using MIT-DB-NSR and MIT-BIH Long-Term ECG signal records in QT-database [16]. In MIT-DB-NSR and MIT-BIH Long-Term ECG database, there are 15 records annotated by the experts and standard automatic algorithms. All records are sampled at 250 Hz, and are normalized to remove changes of amplitude level in

ECG. In addition, the presented algorithms was carried out on the whole QT database in order to compherensively compare the other studies published in later.

The algorithm was performed on the database given above. In the first place, the CWT is applied on the ECG signal in order to get the fiducial points such as Q and R points. The Figure 5 illustrates how the algorithm works..
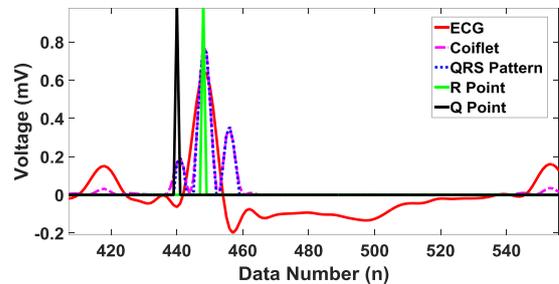
Fig. 5. Q and R point detection

In Figure 5, X and Y axis represent the data number and the voltage value in ECG. The coiflet pattern obtained by CWT was transformed into QRS pattern shown by three peaks on ECG. The first and second marks are assigned as Q and R point, respectively.

Then the algorithm should find where T peak occurs before obtaining the T wave end location. Figure 6 schematically shows the algorithm's annotation.
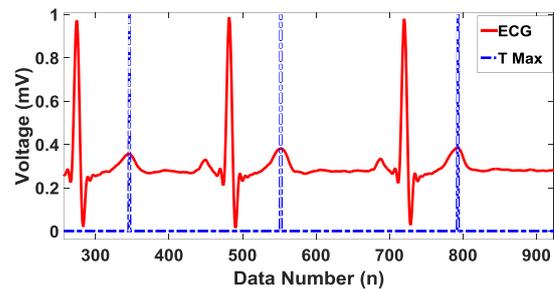
Fig. 6. T wave maximum marking

In Figure 6, the T wave maximum is obtained by searching maximum on refractory period produced by computing RR interval at each cycle.

Finally, T wave end point is marked by evaluating Coiflet pattern in terms of sequential peaks. Figure 7 clearly explains the marking process on ECG signal.
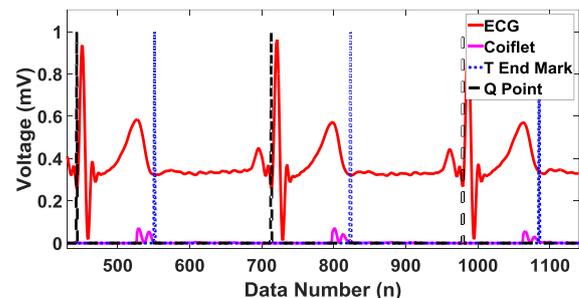
Fig. 7. T Wave End Detection

In Figure 7, Coiflet patterns are only placed at right hand side of T maximum because of erased peaks before T maximum happens. It can be shown that T wave end is

generally found between the third and the second peaks of Coiflet patterns. Actually, Coiflet patterns were established by nine individual frequency regions, which means that each of the frequency regions had a specific sub-signal on ECG illustrating the feature of depolarization and repolarization of the time-related action potential. On the graph (Figure 7), it could be understood that each coiflet peak happens when the sign of derivative of ECG wave changes. This led us to estimate where the repolarization was finished and started. The detailed information has been given in the Method section of this article.

The proposed algorithm applied on the all databases had the scores illustrated in Table 1.

	Manual	Automatic
Mean Error	19.22 ms	15.17 ms
RMS Error	20.22 ms	17.19 ms

Table 1. Test Results

Table 1 shows manual and automatic measurement errors in the tests. According to these results, the manual tests had poor score than automatic tests because manual annotation was only chosen at representative beats which characterize individual cardiac status of patients and had the same patterns. Also, electrophysiologists almost marked the points indicating T wave end before the algorithm one [17]. This led to a great difference in mean error representing how much the algorithm was effective.

The automatic test was performed on all ECG records including broken patterns by using ECGPUWAVE method which had a challenging performance. These results are deeply discussed in the next section.

4. Discussion

In this study, a novel fully automated method was proposed to analyze QT interval in ECG signals. The algorithm achieved QRS complex recognition, finding T-wave peaks and end points in all records. All ECG records were obtained from QT-database which were annotated by the experts and automatic algorithm. However, QT-database contained five different abnormality groups which were not included in this study.

European ST-T Databases included many different patients with myocardial infraction, cardiac artery diseases and hypertension causing ST elavation and rippling isoelectric baseline in ECG. Generally, V4-V5 channels of ECG were used to collect cardiac signals. Due to these reasons, CWT produced a lot of wrong results in the tests. There was no consensus where the T-wave peaks were even in a standard automatic algorithm. Besides, the respiration which was a primary cause of a low frequency noise was not stable in these patient groups. The collision between respiration and T wave end gave many negative results.

We could not include the results from MIT-BIH Supraventricular arrhythmia database, because of their different sampling frequencies. Although the transformation in the sampling frequency was done, there was only one annotation marked by only one cardiologists. So, this database was not included in this study due to much more requirement in control of the proposed algorithm.

Records from Sudden Death patients in BIH database had different T wave morphology, positive negative T-wave. The proposed algorithm was utilized at only positive or only negative T-wave morphology. Nevertheless, these databases results had poor results obtained by standard automatic annotations. In addition, T-wave morphology was not easily discriminated even by observation. As the same way, MIT-BIH ST change database contains records with the high heart rate, so, the ripple in the signal is too high level. MIT-BIH Arrhythmia database was sampled at a different frequency, and contained a different T-wave morphology which our algorithm could not be applied. Additionally, these databases consisted of many premature ventricular contraction (PVC) records which meant that RR interval mostly changed causing to impact on QT interval variation, and the proposed algorithm performance too.

On the other hand, the proposed algorithm did not require the determination of isoelectric level. The algorithm searched specific frequency energy which included T-wave end. The algorithm was not affected by the amplitude level, but frequency changes. It discriminated T-wave positive or negative peaks in MIT-BIH-NSR and Long-term records. Additionally, the decision mechanism related to finding T-wave positive-negative was mostly affected by Q points deflection, because some of the changes such as ST-T elevation and PVC shifted the level of Q points. Mostly, the other database errors were also caused because of that.

Up to now, several studies have been performed to extract T wave end information from QT database [2,10,18,19,20,21,22,23]. The related results are given in Table 2.

	Mean Error	Standard Deviation
Laguna et. al.	18.86	29.79
Cesari et. al.	-0.6	22.3
Leon et. al.	-0.12	15.06
Madeiro et. al.	2.8	15.3
Manriquez et. al.	0.57	22.81
Martinez et. al.	-1.6	18.1
Vila et. al.	-2.7	28
Zhang et. al.	0.31	17.43
Present Work (only MIT-NSR)	0.92	8.72
Present Work (whole QT database)	1.01	12.44

Table 2. Comparison between The Published Algorithm

Table 2 shows the important information about the automatic algorithm. Laguna et. al. [18] used threshold detector in order to make a simple and effective algorithm on Holter device. The results could not efficiently be performed because of the real time application. Manriquez et. al. [21] applied likelihood ratio to detect T wave end, however, their study used multiple ECG signals. Some of the methods were based on wavelet approach [19,22]. In spite of high performance on T wave end location, there

were no standard measurement results in order to compare that their algorithm were clinically acceptable or not. Generally, the derivative methods were simple and effective in non-noisy conditions[2,18]. However, there were too much operations to process the ECG signals, such as requirement of isoelectric level, T wave slope and maximum points changes. The other algorithms reported were implemented on neural network and mathematical modeling. So, the training and comparing phase are highly expensive, and also not fully automated algorithm.

The proposed algorithm was tested on two conditions: only for MIT-BIH-NSR and MIT-Long Term records, and the whole QT database. The performance of the algorithm was quite sufficient in MIT-BIH-NSR and Long-term records due to proper waveform characteristics of ECG signals. However, the measurement performance in evaluating the whole QT database was degraded by some erroneous properties such as different T wave form, absent or corrupted waveform, excessive noise, etc. In spite of all disadvantages mentioned earlier, the whole QT database evaluation results attained high performance classification.

Up to now, the standard algorithms for the detection of QT interval were extensively studied. However, the standard methods are not useful to produce clear information about the cardiac situation of the patient under some dangerous conditions. Some of the diseases, especially in Long QT syndrome causing sudden cardiac death, the standard deviation of the measurement error for detecting the illness is so low which the existing algorithms does not meet this criteria. The presented algorithm can be performed with the standard deviation of 8.72 milliseconds while comparing the expert results. It is concluded that the suggested algorithm provide a better information in comparison with the previous studies.

On the other hand, all studies given by references were differently evaluated in terms of mean and standard deviation error. The calculation of the mean error was done by summing all of the time errors between annotation and the algorithm regardless of their sign. This led to zero mean error if the number of positive mean error equal to negative ones. For this reason, the proposed algorithm was evaluated by using the standard measurement given in [17]. According to this study, absolute mean error and standard deviation error could be acceptable as 15 milliseconds and 20 milliseconds, respectively. As a result, the proposed algorithm could be considered as a diagnostic tool in clinical applications.

Generally, manual tests had poor scores due to lack of representative beat selections. Additionally, automatic algorithm results may be improved by adding representative beat controls in the classification process.

5. Conclusions

In this study, a fully automated technique based on CWT was proposed to measure QT intervals in various ECG signal patterns. Especially, marking T-wave end is the most difficult problem. In this study, CWT was firstly applied on the ECG signals to detect Q position, and then T-wave end location was obtained by the algorithm. The proposed algorithm had achievements both at 15.17 ms mean error and 17.19 ms RMS error in the automatic test and at 19.22 ms mean error and 20.22 ms RMS error in the manual test.

The proposed algorithm does not need any training data, or manual intervention, and also was not influenced by isoelectric level changes and intra-beat variations. However, it is only performed on only positive or only negative T-wave morphologies. Moreover, All QT-databases were not included in the tests because of the existence of different abnormalities and the restrictions on the present algorithm.

In the future work, RR interval changes and selective representative will be added to the algorithm. Additionally, six different T-wave morphologies will be examined to update the algorithm.

In conclusion, the results showed that the proposed algorithm can be effectively used to attain a high performance in the determination of QT intervals automatically.

6. References

[1] Goldberg, R. J., Bengtson, J., Chen, Z., Anderson, K. M., Locati, E., & Levy, D.,"Duration of the QT interval and total and cardiovascular mortality in healthy persons (The Framingham Heart Study experience)".,The American journal of cardiology, 67(1), 55-58.,1991

[2] Zhang, Q., Manriquez, A. I., Médigue, C., Papelier, Y., & Sorine, M.,"An algorithm for robust and efficient location of T-wave ends in electrocardiograms",*IEEE Transactions on Biomedical Engineering*, 53(12), 2544-2552,2006.

[3] Goldenberg, I. L. A. N., Moss, A. J., & Zareba, W. QT interval: how to measure it and what is" normal". *Journal of cardiovascular electrophysiology*, *17*(3), 333-336, (2006).

[4] Helfenbein, E. D., Zhou, S. H., Lindauer, J. M., Field, D. Q., Gregg, R. E., Wang, J. J., ... & Michaud, F. P. An algorithm for continuous real-time QT interval monitoring. *Journal of electrocardiology*, *39*(4), S123-S127, (2006).

[5] Murray, A., McLaughlin, N. B., Bourke, J. P., Doig, J. C., Furniss, S. S., & Campbell, R. W.,"Errors in manual measurement of QT intervals",*British Heart Journal*, 71(4), 386-390, 1994.

[6] McLaughlin, N. B., Campbell, R. W. F., & Murray, A.,"Accuracy of automatic QT measurement techniques". *Computers in Cardiology*, Proceedings. 863-866. IEEE, 1993.

[7] Hayn, D., Kollmann, A., & Schreier, G.,"Automated QT interval measurement from multilead ECG signals",*Computers in Cardiology*, 381-384, IEEE, 2006.

[8] Clifford, G. D., & Villarroel, M. C.,"Model-based determination of QT intervals",*Computers in Cardiology*, 357-360, IEEE, 2006.

[9] Xue, Q., & Reddy, S. Algorithms for computerized QT analysis. *Journal of electrocardiology*, *30*, 181-186. (1998).

[10] Alexander A. Suarez Leon et al, "Neural Network Approach for T wave End Detection: A comparison of Architectures", Comput. Cardiol., vol. 42, pp. 589-592, 2015.

[11] Mehmet İşcan; Cüneyt Yilmaz; Faruk Yiğit, " T-wave end pattern classification based on Gaussian mixture model", DOI: 10.1109/SIU.2016.7496149, Pages 1953 - 1956, 2016.

[12] Mehmet İşcan, Faruk Yiğit, Cüneyt Yilmaz," Heartbeat Pattern Classification Algorithm Based on Gaussian Mixture Model", Inter. Symp. on Med. Meas. and App., Italy,2016.

[13] Chesnokov, Y. C., Nerukh, D., & Glen, R. C.,"Individually adaptable automatic QT detector". *Computers in Cardiology*,337-340, IEEE, 2006.

[14] Li, C., Zheng, C., & Tai, C. Detection of ECG characteristic points using wavelet transforms. *IEEE Transactions on biomedical Engineering*, *42*(1), 21-28., (1995).

[15] Chudacek, V., Huptych, M., Novak, D., & Lhotska, L.. Automatic QT interval measurement using rule-based gradient method. In *Computers in Cardiology, 2006* (pp. 349-351). IEEE, (2006, September)

[16] Laguna P. R. G. Mark, Goldberger A., Moody G. B., "A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG", *Comput.in Card.*, 1997.

[17] Willems, J. L., Abreu-Lima, C., Arnaud, P., van Bemmel, J. H., Brohet, C., Degani, R., ... & Machado, H. The diagnostic performance of computer programs for the interpretation of electrocardiograms. *New England Journal of Medicine*, *325*(25), 1767-1773., (1991).

[18] Jané, R., Blasi, A., García, J., & Laguna, P.. Evaluation of an automatic threshold based detector of waveform limits in Holter ECG with the QT database. In *Computers in Cardiology 1997* (pp. 295-298). IEEE., (1997, September)

[19] Cesari, M., Mehlsen, J., Mehlsen, A. B., & Sorensen, H. B. D. Application of a new robust ECG T-wave delineation algorithm for the evaluation of the autonomic innervation of the myocardium. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the* (pp. 3801-3804). IEEE, (2016, August).

[20] Madeiro, J. P., Nicolson, W. B., Cortez, P. C., Marques, J. A., Vázquez-Seisdedos, C. R., Elangovan, N., ... & Schlindwein, F. S. New approach for T-wave peak detection and T-wave end location in 12-lead paced ECG signals based on a mathematical model. *Medical engineering & physics*, *35*(8), 1105-1115., (2013).

[21] Manriquez, A. I., Zhang, Q., Medigue, C., Papelier, Y., & Sorine, M. Multi-lead T wave end detection based on statistical hypothesis testing. *IFAC Proceedings Volumes*, *39*(18), 93-98., (2006).

[22] Martínez, J. P., Almeida, R., Olmos, S., Rocha, A. P., & Laguna, P. A wavelet-based ECG delineator: evaluation on standard databases. *IEEE Transactions on biomedical engineering*, *51*(4), 570-581., (2004).

[23] Vila, J. A., Gang, Y., Presedo, J. M. R., Fernández-Delgado, M., Barro, S., & Malik, M. A new approach

for TU complex characterization. *IEEE Transactions on Biomedical Engineering*, *47*(6), 764-772., (2000).

Note:

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Cüneyt Yılmaz was born in Beykoz, Istanbul. He studied Mechanical Engineering in Istanbul Technical University. After he got his masters degree, he went to the United States for his PhD education. After he got his PhD degree, he worked in University of Texas Southwestern Medical Center's Pulmonary laboratories as a senior research engineer, research faculty and assistant professor. After 17 year experience in the United States, he returned back to his native country, Turkey. He has been a faculty member of the Mechatronics Engineering Department of Yıldız Technical University Mechanical Faculty for about 3 years.